# Detection of Carotid Artery from Pre-Processed Magnetic Resonance Angiogram

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***Abstract*—Boundary detection is playing an important role in the medical image analysis. In certain cases it becomes very difficult for the doctors to assess the carotid arteries from the magnetic resonance angiography (MRA) of the neck. In this paper an attempt has been made to detect carotid arteries from the neck magnetic resonance angiograms, so as to overcome such difficulties. The algorithm pre-processes the magnetic resonance angiograms and subsequently detects the carotid artery. Stenosis is expected to reduce the diameter of the vessel. The diameter can be measured from the vasculature detected image. As the algorithm successfully detects the carotid artery from the neck magnetic resonance angiograms, therefore it will help doctors for diagnosis and serve as a step in the prevention of cardiovascular diseases.**

***Index Terms*—magnetic resonance angiogram, pre-processing, carotid artery detection, cardiovascular diseases, medical image analysis**

## I. Introduction

Magnetic resonance angiography (MRA) is a way to study vascular structures through the use of a Gadolinium based contrast agent, Gd-DTPA [1, 3]. A patient is injected with contrast during scanning, and images are captured during the arterial phase. Arteries appear bright on the image whereas other structures without the contrast appear darker. These images are used to diagnose the vasculature diseases such as stenosis [1, 2]. This technique has several advantages over conventional digital subtraction angiography (DSA).

The magnetic resonance angiograms of neck which is acquired for detection and diagnosis of carotid arterial disease is also called carotid artery stenosis. The term refers to the narrowing of carotid arteries due to deposition of fatty substances and cholesterol. The stenosis or occlusion refers to the blockage of the artery. When the carotid arteries are obstructed, it leads to increased risk for a stroke [4]. A stroke may occur if the artery becomes extremely narrowed or breakage of a piece of plaque and travels to the smaller arteries of the brain or even formation of clot which may block a narrowed artery. A stroke is similar to a heart attack, which occurs when the brain cells are devoid of oxygen and sugar carried to them by blood. If the lack of blood flow lasts for 3 to 6 hours, the damage is permanent [5]. There may be no symptoms for carotid artery disease.

A magnetic resonance angiography (MRA) of the neck inthe non-invasive mode is performed to identify the narrowing of the carotid arteries [6, 7]. Our proposed algorithm significantly detects the carotid artery from the pre-processed magnetic resonance angiogram, which will assist the doctors to analyze the carotid arterial disease from the vasculature detected image without any difficulty.

## II. Materials and Methods

### A. *Pre-processing Techniques*

Histogram equalization is a spatial domain image enhancement technique that modifies the distribution of the pixels to become more evenly distributed over the available pixel range [8]. In histogram processing, a histogram displays the distribution of the pixel intensity values, mimicking the probability density function (PDF) for a continuous function. An image that has a uniform PDF will have pixel values at all valid intensities. Therefore, it will show a high contrast image. Histogram equalization creates a uniform PDF or histogram [9]. This can be accomplished by performing a global equalization that considers all the pixels in the entire image or a local equalization that segments the image into regions.

In case of the negative of an image, enhancement of white or gray details in a dark background occurs [9]. A negative image is calculated using (1),

$$P = (L - 1) - I \qquad (1)$$

Where P is the new pixel value, L is the number of new pixel values and I is the original pixel intensity [8].

Subtraction images may also cause enhancement of certain regions of an image. In contrast enhanced MRA, a mask image is used and subtracted from a contrast enhanced image to boost up the contrast [10].

### B. *Edge Detection*

The edge detection process detects outline of an object and boundaries between objects and the background in the image. The edge-detection operation is performed by forming a matrix centered on a pixel chosen as the center of the matrix area [11]. If the value of this matrix area is above a given threshold value, then the middle pixel is considered to be as an edge. Examples of gradient based edge detectors are Sobel and Prewitt operators. The gradient-based algorithms have kernel operators that calculate the strength of the slope in directions which are orthogonal to each other, commonly vertical and horizontal. Later, the different components of the slopes are combined to give the total value of the edge




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strength [8].The first-order derivative of an intensity, f(x, y), of an image is the gradient. The gradient is defined as the vector as shown in (2).

$$\nabla f = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \partial f/\partial x \\ \partial f/\partial y \end{bmatrix} \tag{2}$$

The magnitude of the vector is given in (3).

$$\nabla f = \mathrm{mag}(\nabla f) = \left[G_x{}^2 + G_y{}^2\right]^{1/2} = \left\{\left(\partial f/\partial x\right)^2 + \left(\partial f/\partial y\right)^2\right\}^{1/2} \tag{3}$$

The gradient vector, points in the direction of the maximum rate of change of the 2-D function f(x, y), of an image. The angle at which this maximum rate of change occurs is mathematically shown in (4).

$$\alpha(x, y) = \tan^{-1}\left(G_y/G_x\right) \tag{4}$$

There are various approaches as mentioned in this section to determine the derivatives $G_x$ and $G_y$ digitally. The second-order derivatives of the intensity, f(x, y), of an image are computed using the Laplacian equation as given in (5).

$$\nabla^2 f(x, y) = \frac{\partial^2 f(x,y)}{\partial x^2} + \frac{\partial^2 f(x,y)}{\partial y^2} \tag{5}$$

*1) Sobel Operator*

The Sobel operator performs a 2-D spatial gradient measurement on an image. It is used to find the approximate absolute gradient magnitude at each point in an input grayscale image [12]. Fig. 1 shows the 3x3 area representing the gray levels of an image. The operator consists of a pair of 3×3 convolution masks as shown in Fig. 2. One mask is simply the other rotated by 90° [8, 11-12].

| | | |
|---|---|---|
| $Z_1$ | $Z_2$ | $Z_3$ |
| $Z_4$ | $Z_5$ | $Z_6$ |
| $Z_7$ | $Z_8$ | $Z_9$ |

Figure1. Image Neighborhood

| | | |
|---|---|---|
| -1 | 0 | +1 |
| -2 | 0 | +2 |
| -1 | 0 | +1 |

Gx

| | | |
|---|---|---|
| +1 | +2 | +1 |
| 0 | 0 | 0 |
| -1 | -2 | -1 |

Gy

Figure2. Sobel convolution masks

The detector uses the masks to compute the first order derivatives $G_x$ and $G_y$, as shown in (6).

$$G_x = Z_7+2Z_8+Z_9$$
$$G_y = Z_1+2Z_2+Z_3 \tag{6}$$

*II) Prewitt Operator*

The Prewitt operator as similar to the Sobel measures two components. The vertical edge component is calculated with kernel Gx and the horizontal edge component is calculated with kernel Gy, as shown in (7).

$$G_x = (Z_7+Z_8+Z_9)-(Z_1+Z_2+Z_3)$$
$$G_y = (Z_3+Z_6+Z_9)-(Z_1+Z_4+Z_7) \tag{7}$$

In the mentioned formulation, the difference between the first and third rows of the 3x3 image region as show in Fig. 1 approximates the derivative in the x-direction, and the difference between the third and first columns approximates the derivative in the y-direction [8, 11, 12]. The Prewitt masks as shown in Fig. 3 are used to implement $G_x$ and $G_y$.

| | | |
|---|---|---|
| -1 | 0 | 1 |
| -1 | 0 | 1 |
| -1 | 0 | 1 |

$G_x$

| | | |
|---|---|---|
| 1 | 1 | 1 |
| 0 | 0 | 0 |
| -1 | -1 | -1 |

$G_y$

Figure3. Prewitt masks

*III) Canny Operator*

The Canny edge detection algorithm is known as an optimal edge detector based on a set of criteria which include finding the most edges by minimizing the error rate, marking edges as closely as possible to the actual edges to maximize localization, and marking edges only once when a single edge exists for minimal response [13].

The first stage involves smoothing the image by convolving with a Gaussian filter. This is followed by computing the gradient of the image by feeding the smoothed image through a convolution operation with the derivative of the Gaussian in both the vertical and horizontal directions [8, 11].

| | | |
|---|---|---|
| -1 | 0 | +1 |
| -2 | 0 | +2 |
| -1 | 0 | +1 |

Gx

| | | |
|---|---|---|
| +1 | +2 | +1 |
| 0 | 0 | 0 |
| -1 | -2 | -1 |

Gy

Figure4. Canny convolution masks

*1V) Laplacian of Gaussian Operator*

The Laplacian of an image highlights regions of rapid intensity change and is therefore often used for .edge detection [8]. The Laplacian is applied to an image that has first been smoothed with Gaussian filter in order to reduce its sensitivity to noise. The operator takes a single gray level image as input and produces another gray level image as output.

| | | |
|---|---|---|
| 0 | 1 | 0 |
| 1 | −4 | 1 |
| 0 | 1 | 0 |

| | | |
|---|---|---|
| 1 | 1 | 1 |
| 1 | −8 | 1 |
| 1 | 1 | 1 |

| | | |
|---|---|---|
| −1 | 2 | −1 |
| 2 | −4 | 2 |
| −1 | 2 | −1 |

Figure5. Laplacian of Gaussian kernels

The kernels that are mentioned in Fig. 5 are used as discrete approximations to the Laplacian filter [8, 12]. The 2-D LoG function centered on zero and with Gaussian standard deviation ó has the form as shown in (9).

$$\mathrm{LoG}(x, y) = -\frac{1}{\pi\sigma^4}\left[1 - \frac{x^2+y^2}{2\sigma^4}\right] e^{-\frac{x^4+y^4}{2\sigma^2}} \tag{9}$$


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The block diagram of our developed algorithm is shown in Fig. 6. The input neck magnetic resonance angiograms are taken from the websites e.g. cedars-sinai.edu, sciencephoto.com, elsevierimages.com, springerimages.com, and imaging.consult.com.

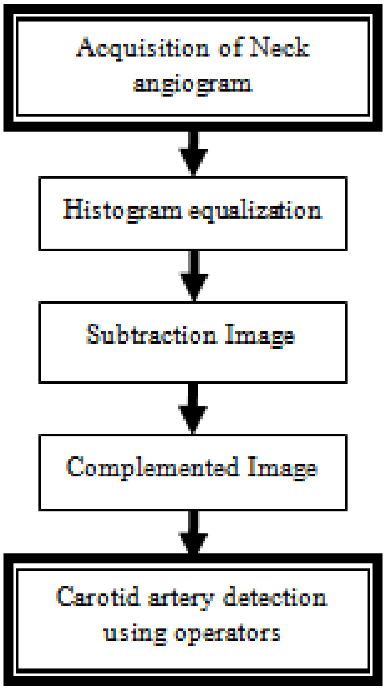


Figure 6. System Block Diagram

The algorithm is developed on MATLAB version 7.6.0(R2008a) in Microsoft Windows XP operating system, with the processor 2.16GHz and 1.96GB of RAM

## III. Results and discussion

Fifteen magnetic resonance angiograms of the neck are used to evaluate the proposed algorithm. Among them three angiograms are shown in Fig. 7(a), Fig. 8(a), and Fig. 9(a) respectively. Initially histogram equalization technique is performed, as shown in Fig. 7(b), Fig. 8(b), and Fig. 9(b) respectively. The original and the histogram equalized images are then converted to double precision images in order to perform the subtraction operation.

Subtraction image is obtained by subtracting the original image from the histogram equalized image, as shown in Fig. 7(c), Fig. 8(c), and Fig. 9(c) respectively. Finally, subtracted image is been complemented for vessel detection, as shown in Fig. 7(d), Fig. 8(d), and Fig. 9(d) respectively. Edge detection operators e.g. Sobel, Prewitt, Canny and Laplacian of Gaussian are used to perform on the complemented image. Carotid artery detection for the test image 1 has been shown in Fig. 10(a), Fig. 10(b), Fig. 10(c) and, Fig. 10(d) respectively using the above mentioned edge detection operators. The developed algorithm automatically calculates the threshold for the images.

### *A. Pre-Processing*

#### *1) Test Image 1*

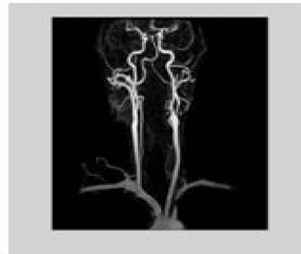

Figure 7(a). Original Image

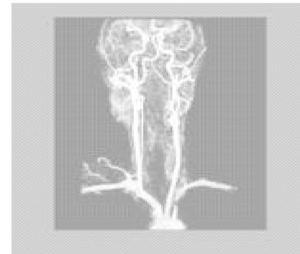

Figure 7(b). Histogram Equalized

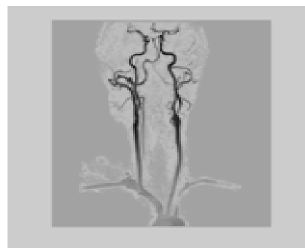

Figure 7(c). Subtracted Image

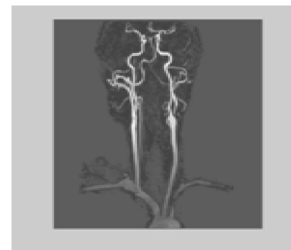

Figure 7(d). ComplementedImage

#### *2) Test Image 2*

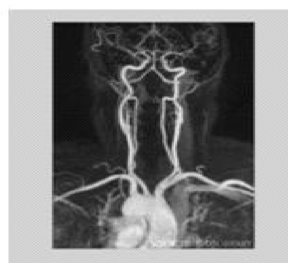

Figure 8(a). Original Image

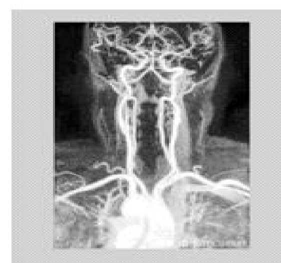

Figure 8(b). Histogram Equalized

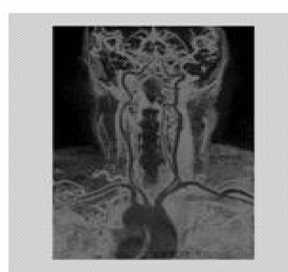

Figure 8(c). Subtracted Image

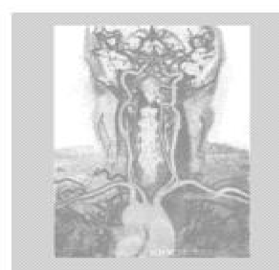

Figure 8(d). Complemented Image

#### *3) Test Image 3*

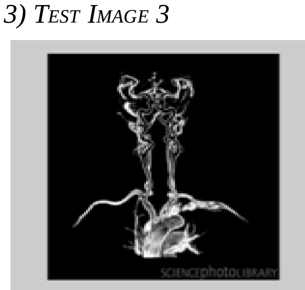

Figure 9(a). Original Image



Figure 9(b). Histogram Equalized




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Figure 9(c). Subtracted Image

Figure 9(d). Complemented Image

Histogram equalization takes advantage of the neglected pixel values and provides better definition and more information for the doctors. Complement of the subtracted images provided a better means to assess carotid arteries that were not as clear in the original magnetic resonance angiograms. The histogram equalization increased contrast and provided a better assessment of vasculature. Subtracted images boosted up the result.

### *B. Carotid Artery Detection on Test Image 1*

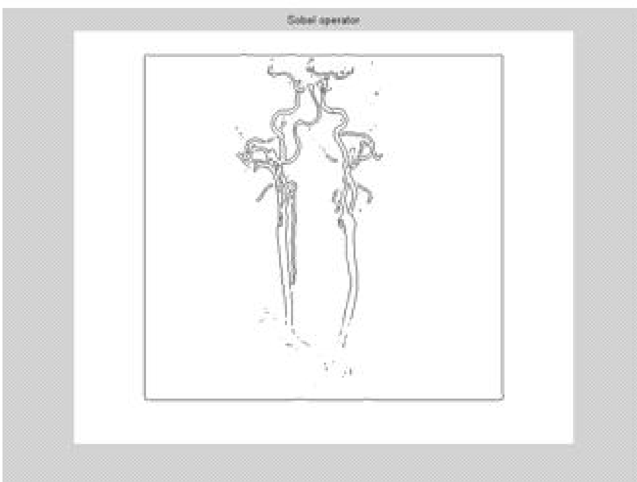


Figure 10(a). Edge detection using Sobel operator

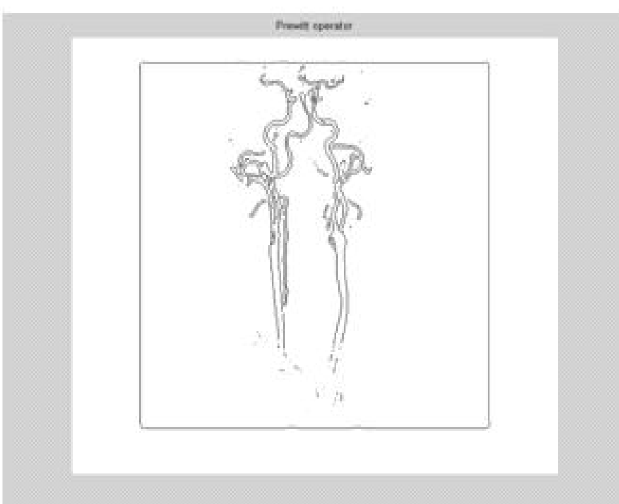


Figure 10(b). Edge Detection using Prewitt operator

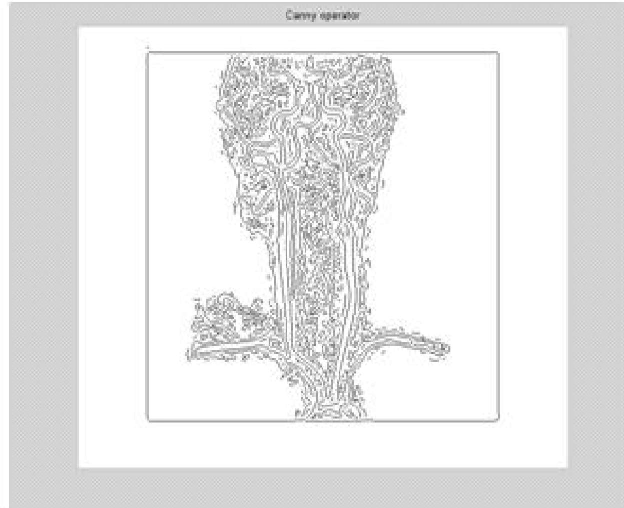


Figure 10(c). Edge detection using Canny operator

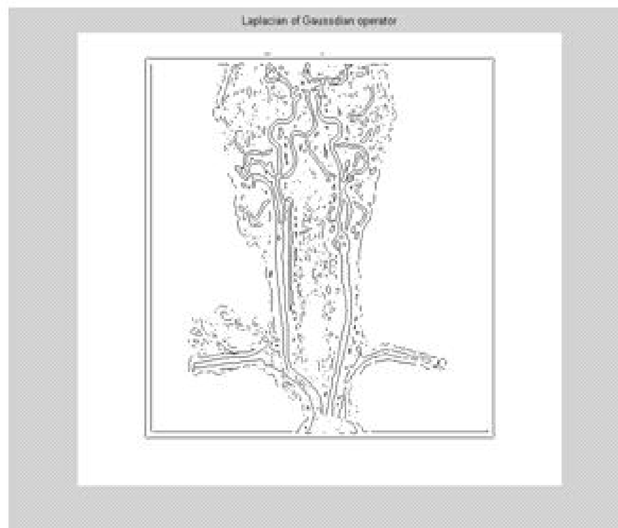


Figure 10(d). Edge detection using Laplacian of Gaussian operator

Edge detection algorithms are able to detect the carotid artery very well. The best algorithm among the Sobel, Prewitt, Canny and Laplacian of Gaussian is the Laplacian of Gaussian operator. This algorithm detects the carotid artery from the neck magnetic resonance angiograms prominently.

## CONCLUSION

The developed method will help doctors to diagnose carotid arteries in a better way by reducing the subjectivity and miss rate in magnetic resonance angiograms of neck and thereby this will enhance the stenosis detection accuracy in less time. It has been found that the performance of Laplacian of Gaussian operator is the best amongst all other operators used in this work. Also, the pre-processing algorithm developed in this work has successfully detected the carotid arteries.




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